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Engineering system co-design with limited plant redesign

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Rather than designing engineering systems from the ground up, engineers often redesign strategic portions of existing systems to accommodate emerging needs. In the redesign of mechatronic systems, engineers typically seek to meet the requirements of a new application via control redesign only, but this is often insufficient and physical system (plant) design changes must be explored. Here, an integrated approach is presented for the redesign of mechatronic systems involving partial plant redesign that avoids costly complete redesign. Candidate plant modifications are identified using sensitivity analysis, and then an optimization problem is solved that minimizes redesign cost while satisfying system requirements. This formal methodology for Plant-Limited Co-Design (PLCD) is demonstrated using a robotic manipulator design problem. The PLCD result costs significantly less than the full redesign, and parametric studies illustrate the tradeoff between redesign cost and performance. It is shown that the proposed sensitivity analysis results in the lowest cost limited redesign.

Keywords: design optimization; robotics; passive dynamics; control; energy efficiency

1. Introduction

The work presented here is part of a broader effort to enhance the ability to redesign or reconfigure engineering systems, which is becoming increasingly important as the scale and complexity of engineering systems increases (Siddiqi and de Weck 2008; de Weck *et al.* 2011). Completely redesigning and reimplementing large-scale engineering systems as needs evolve is impractical, especially in the case of systems-of-systems, such as transportation or energy systems (DeLaurentis 2005). Engineers must learn to manage the persistence of legacy system components that are too costly to replace, while strategically modifying other system elements to achieve the desired functionality and performance in the most cost effective way (Harper and Thurston 2008). Formal methods for strategic limited redesign are thus emerging as a critical segment of engineering system design; an especially important aspect of these methods involves the identification of candidate system modifications. The focus of this article is on one specific type of strategic redesign: modification of mechatronic systems to meet new needs at minimal plant modification cost.

Engineering systems often incorporate active control systems to govern dynamic behaviour. The design of a physical system and the design of its control system are interdependent activities (Fathy 2003). Conventional sequential design approaches (Li *et al.* 2001; Friedland 1996; Roos 2007) usually produce suboptimal results (Reyer *et al.* 2001). A class of design methodologies, known as

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co-design, accounts for physical system and control system design coupling and produces system-optimal results. Existing co-design strategies are intended for cases where the physical system does not already exist and the system designer has complete freedom to specify both physical and control system design (*i.e.*, clean-sheet design). In practice, however, engineers are often faced with design problems where the physical system (plant) has already been manufactured; in this case the design objective is either to design a control system that enables the plant to be used for a new purpose, or to improve performance for its original purpose. Often control design changes alone are insufficient to meet performance requirements for the new system application, *i.e.*, the desired performance cannot be achieved due to fundamental physical limitations that are independent of control design. For example, kinematic restrictions, excessive structural compliance, mismatched natural frequencies, or inadequate actuators may prevent a system from performing a task in an acceptable manner even after extensive control design studies.

Open-loop optimal control methods that are not restricted by control structure, such as direct transcription (Biegler 2010) or dynamic programming (Denardo 1982), may be used to confirm whether any input control trajectory is capable of satisfying the new task requirements via control design alone. If no feasible trajectories exist, limited plant modifications should be explored to identify efficient plant design changes that enable requirement satisfaction. Modifying already manufactured physical systems is costly, so minimizing the number and complexity of these modifications is essential. This can be addressed in a systematic manner through Plant-Limited Co-Design (PLCD), which is a new design methodology that produces system-optimal designs with minimum-cost plant modifications while satisfying performance requirements for new system applications.

Many elements of system redesign have been investigated, including strategies for evaluation of the original system and deciding whether redesign should be performed, as well as methods for determining appropriate system modifications. System redesign has been explored across several application domains, such as manufacturing systems (Serrano *et al.* 2008), dynamic structural systems (Takewaki 1997), and, most notably, control system design (Ioannou and Kokotovic 1984; Looze *et al.* 1985; Taranto *et al.* 1995; Khalil 1996; Boyle 2003), although none has involved co-design.

Some cite failure (Looze *et al.* 1985), impending failure (Vachtsevanos *et al.* 2007), or poor performance (Liker 2003) as criteria for choosing to redesign a system, whereas the emphasis of the PLCD method presented here is on modifying systems that are being re-purposed for new applications. PLCD can help support the continued utilization of large-scale engineering systems that often outlive their originally intended function due to dynamically changing needs (Harper and Thurston 2008). System redesign has also been studied as part of the iterative product development process (Mistree *et al.* 1981; Dixon *et al.* 1987; Boyle 2003); this type of redesign is different from PLCD because the system has not already been manufactured.

Once it is recognized that a system must be redesigned, the first step is to identify appropriate candidate design changes. This may be accomplished through domain-specific rules or heuristics (Finger and Dixon 1989; Boyle 2003), optimization-based methods (Mistree *et al.* 1981; Kim *et al.* 2004), or knowledge-based systems (Boyle 2003). Prognostics and health management studies have also been used in cases where predicted system failure must be prevented through system enhancements (Vachtsevanos *et al.* 2007). In this article a formal sensitivity-based approach coupled with optimal co-design is proposed for determining least-cost plant design modifications that satisfy requirements for a new system application.

The following sections outline and demonstrate a proposed methodology for PLCD. The special challenges of developing models suitable for exploring physical system design changes is discussed, and a sensitivity analysis approach is introduced that helps limit the scope of the plant design problem and the associated system model. A two-link robotic manipulator design problem is then used to demonstrate the application of PLCD to mechatronic systems. An baseline manipulator design is obtained using co-design that minimizes energy consumption for a specific pick-and-place task. This initial system design capitalizes on passive system dynamics to improve energy efficiency. Next, a second task is introduced that cannot be performed using the baseline design without plant modifications. The manipulator is redesigned using PLCD, and it is shown that a limited redesign can produce an energy efficient design at significantly reduced cost compared to full system redesign. PLCD is demonstrated to be an effective approach for solving an important class of mechatronic design problems that have not yet been studied in a formal way.

2. Plant-Limited Co-Design (PLCD)

PLCD is a new mechatronic system design methodology where limitations on plant design modifications are accounted for explicitly. PLCD problems arise when engineers seek to re-purpose existing systems for new applications. For example, an existing directional antenna designed originally for maintaining a line-of-sight radio connection between a ship and aircraft might be modified to maintain a connection between a land vehicle and aircraft. The vehicle dynamics are significantly different between these two situations, and the original system may not meet performance requirements for the new system application. Suppose, after exhaustive control system analysis, engineers conclude that system performance requirements for the new application cannot be met through control design changes alone. Designing a new physical system from scratch would be a familiar, yet expensive, solution to this problem. An alternative strategy involves exploring limited changes to the existing plant design to determine if system performance requirements can be met at a reasonable cost. This strategy requires an integrated design approach where limited plant redesign is considered simultaneously with control system design. Otherwise, it would not be possible to identify which elements of a physical system could be modified to meet the new requirements at minimum cost.

This article presents one possible method for solving the PLCD problem based on optimization. It is a multidisciplinary design optimization approach with two disciplines: physical system design and control design (Allison and Nazari 2010; Allison and Han 2011). Other approaches are possible and opportunities for future work in this emerging area of mechatronic system design are identified in later sections.

2.1. *PLCD solution process*

Here, a formal optimization-based approach is proposed for solving PLCD problems. The following is an outline of the solution process.

Step 1. Identify candidate plant modifications.
Step 2. Develop a system model with independent variables in the selected plant and control design spaces.
Step 3. Formulate and solve the PLCD optimization problem.
Step 4. Verify the result and repeat if further improvement can be made via alternative plant modifications.

In the first step the system is analysed to determine which aspects of the plant should be modified. Here a sensitivity-based approach is proposed for identifying plant modifications that are likely to have significant impact on system performance. Once this is done, a system model can be developed that provides sufficient flexibility for exploring the selected candidate plant and control design modifications. With a complete system model established, the PLCD optimization problem may be formulated and solved. This article presents two approaches for solving the PLCD optimization problem. In the first, plant modification cost is minimized while meeting system performance constraints. In the second approach, the tradeoff between plant modification expense and system performance improvement is explored using a multi-objective formulation. After solving the PLCD problem, the result may be examined to determine whether further improvement can be achieved by altering the set of candidate plant modifications. If this is the case, the process can be repeated. The following sections describe each of these steps in detail.

2.2. *Plant modification analysis*

In solving a PLCD problem, engineers may consider several different types of plant design changes, such as actuator choice, component replacement or modification, component removal or relocation, addition of new components, or other topological changes. These modifications can have a significant effect on dynamic properties. A primary objective in solving PLCD problems is to identify efficient plant modifications that enable requirement satisfaction with minimal expense and effort. Narrowing down the set of candidate plant changes eases both modelling and optimization challenges.

Here, a first-order approach is presented for analysing the link between plant characteristics and system performance. This analysis may be used to select a set of candidate plant changes that form the basis of the system redesign model and PLCD optimization problem. This sensitivity-based approach applies only to candidate plant changes that are continuous in nature, such as continuous geometric changes to existing components. Design objectives and constraints must be differentiable with respect to candidate plant modifications. Future work will address discrete modifications, such as the addition or reconfiguration of plant components, using promising techniques such as topological derivatives (Novotny *et al.* 2005; Guzina and Chikichev 2007; Amstutz, Takahashi, and Vexler 2008; Mróz and Bojczuk 2012) or generative algorithms (Shea, Aish, and Gourtovaia 2005).

Sensitivity analysis may be performed using a simplified system model, such as a model suitable for control system design. A model that incorporates independent plant design variables, such as geometric dimensions, is not needed at this stage. Rather, the system model may be expressed in terms of parameters that quantify plant characteristics (denoted $\mathbf{p}$ here), such as inertia values or damping rates, which is typical of models developed for control design. A simplified model may have been used for control system design when the original system was developed, and may be available at this stage.

Consider the set of system performance requirements for the new task posed in negative null form: $\mathbf{g_r}(\mathbf{p}) \leq \mathbf{0}$, and a subset of these requirements that the original system was unable to meet or were found to be active constraints: $\bar{\mathbf{g}}_\mathbf{r}(\mathbf{p}) \leq \mathbf{0}$. The sensitivity of $\bar{\mathbf{g}}_\mathbf{r}(\mathbf{p})$ with respect to plant characteristics $\mathbf{p}$ is used to rank and select candidate plant modifications. The rationale here is to identify elements of plant design that can influence system performance as efficiently as possible.

The first sensitivity approach involves the derivatives of the violated requirements for the new system application with respect to plant parameters, *i.e.*

$$\frac{\partial \bar{g}_{ri}(\mathbf{p})}{\partial p_j}, \quad i = 1, 2, \ldots, n_r, \quad j = 1, 2, \ldots, n_p, \tag{1}$$

where n_r is the number of violated requirements and n_p is the number of model parameters. These terms form the model parameter Jacobian $\mathbf{J}_p$, which can be used to identify the most influential parameters. A large absolute value of $\partial \bar{g}_{ri}(\mathbf{p})/\partial p_j$ indicates that requirement i is influenced significantly by small changes in p_j. After a set of influential model parameters $\bar{\mathbf{p}}$ is identified based on $\mathbf{J}_p$, a corresponding set of candidate plant changes $\bar{\mathbf{x}}_\mathbf{p}$ that influence $\bar{\mathbf{p}}$ must be established. Note that $\bar{\mathbf{x}}_\mathbf{p}$ is a subset of variables selected from the full set of plant design variables $\mathbf{x_p}$ corresponding to full system design. The link between $\bar{\mathbf{p}}$ and $\bar{\mathbf{x}}_\mathbf{p}$ may be difficult to establish, requiring change propagation analysis (Giffin *et al.* 2009). Once $\bar{\mathbf{x}}_\mathbf{p}$ is identified, the system model can then be expanded (described in the next step). Model expansion often requires a significant investment, so narrowing down the set of candidate plant changes here is a crucial task.

A more sophisticated analysis for selecting $\bar{\mathbf{x}}_\mathbf{p}$ involves the sensitivity of violated requirements with respect to cost:

$$\frac{\partial \bar{g}_{ri}(\mathbf{p})}{\partial p_j}\left(\frac{\partial C(\mathbf{p})}{\partial p_j}\right)^{-1} = \frac{\partial \bar{g}_{ri}(\mathbf{p})}{\partial c_j}, \quad i = 1, 2, \ldots, n_r, \quad j = 1, 2, \ldots, n_p, \tag{2}$$

where $C(\mathbf{p})$ approximates the cost of changing model parameters, and c_j represents the cost of changing model parameter p_j. This cost model could be based on correlation between cost and these parameters on similar existing systems (Collopy and Eames 2001). The $\partial \bar{g}_{ri}(\mathbf{p})/\partial c_j$ terms form the cost Jacobian $\mathbf{J}_c$, which can be used to assess more accurately which plant modifications could produce the desired performance improvements most economically.

While this step is presented as a component of the larger PLCD process, it may be used alone in conjunction with conventional design methods. For example, once $\bar{\mathbf{x}}_\mathbf{p}$ is identified using sensitivity analysis, engineers can proceed using conventional design methods to modify the plant and then the control system in a sequential manner. In some cases this approach may be sufficient, and the relatively small modelling and analysis investment is appealing. Mattila and Virvalo (2000), for example, applied an informal version of PLCD Step 1 by identifying critical elements of a hydraulic manipulator and redesigning them using conventional techniques to achieve significant energy savings. Observe, however, that this sequential approach is not a co-design method; potential synergy between plant and control design cannot be exploited and the result will not be system-optimal. If this simplified approach is not successful, the full co-design process described above should be used. In addition, if the full co-design process fails to identify a new design that satisfies requirements based on a particular $\bar{\mathbf{x}}_\mathbf{p}$, the criteria for selecting $\bar{\mathbf{p}}$ should be relaxed to increase the dimension of $\bar{\mathbf{x}}_\mathbf{p}$.

2.3. *System model development*

Solving the PLCD optimization problem described in Step 3 requires a system model that has as independent variables the candidate plant modifications $\bar{\mathbf{x}}_\mathbf{p}$ identified in Step 1. At this stage, available models are often limited to those that are appropriate for control design, or formal system descriptions using languages such as SysML (Friedenthal *et al.* 2008). While these models may indeed be useful for supporting candidate plant design variable selection, they are insufficient for supporting the solution of the PLCD optimization problem because they do not provide quantitative performance predictions for modified physical systems. Models that do predict accurately the results of physical system design changes are challenging to develop, often requiring significant resource investment. Developing a system model that accommodates all possible plant changes is impractical and unnecessary for realistic PLCD problems since only part of the plant design is being changed; reducing the dimension of $\bar{\mathbf{x}}_\mathbf{p}$ is important both for curbing model development expense and easing optimization solution difficulty.

One possible modelling approach is to augment the existing control design oriented model used in Step 1 with specialized modelling tools to predict model parameter values. The objective is to form a model $\bar{\mathbf{p}} = \mathbf{a}(\bar{\mathbf{x}}_\mathbf{p})$, where $\mathbf{a}(\bar{\mathbf{x}}_\mathbf{p})$ is an analysis function that computes model parameters as a function of independent plant design variables using computer aided engineering tools (such as finite element analysis). This unidirectional system model structure is described in more detail by Allison and Nazari (2010) and Frischknecht *et al.* (2010). Bidirectional coupling between plant and control design may still be captured through plant design constraint dependence on control design variables $\mathbf{x_c}$.

2.4. *Plant modification minimization*

Once candidate plant modifications $\bar{\mathbf{x}}_\mathbf{p}$ have been identified and a suitably flexible system model has been developed, an optimization-based approach may be used to identify the minimum plant modification required to meet system requirements. Consider the following PLCD optimization problem:

$$\begin{aligned} \min_{\mathbf{x}=[\bar{\mathbf{x}}_\mathbf{p}^\mathrm{T},\mathbf{x}_\mathbf{c}^\mathrm{T}]^\mathrm{T}} \quad & \phi(\mathbf{x}) \\ \text{s.t.} \quad & \mathbf{g_p}(\mathbf{x}) \leq 0 \\ & \mathbf{g_r}(\mathbf{x}) \leq 0, \end{aligned} \tag{3}$$

where $\phi(\mathbf{x})$ is a measure of deviation from the original plant design, $\mathbf{g_p}(\mathbf{x})$ are plant design constraints, and $\mathbf{g_r}(\mathbf{x})$ are system performance requirements formulated as inequality constraints. Both sets of constraints are assumed to be given here. Note that $\mathbf{g_r}(\mathbf{x})$ represents the full set of system requirements, not just those used in Step 1 for identifying candidate plant modifications. While omitted from this formulation, control design constraints such as stability may be included here. The optimization variable $\bar{\mathbf{x}}_\mathbf{p}$ parametrizes the candidate plant modifications, and $\mathbf{x_c}$ are the control design variables. The solution to this problem is a system design that meets performance requirements for the new task while requiring minimal modifications to the physical system design. Note that multiple new tasks could be considered in PLCD by combining requirements for each task into $\mathbf{g_r}(\mathbf{p})$ and performing a separate simulation for each task, or by using a multi-objective formulation to investigate performance tradeoffs among tasks.

The choice of metric $\phi(\mathbf{x})$ has significant impact on the resulting design solution. A weighted norm on the difference between the original design $\bar{\mathbf{x}}_\mathbf{0}$ and the new design $\bar{\mathbf{x}}_\mathbf{p}$ (*i.e.*, $\phi(\mathbf{x}) = \|\mathbf{w} \circ (\bar{\mathbf{x}}_\mathbf{0} - \bar{\mathbf{x}}_\mathbf{p})\|$) might be used as a simplified metric. The variable weights $\mathbf{w}$ help account for varying difficulty in different plant modifications as well as the magnitude of the components of $\bar{\mathbf{x}}_\mathbf{p}$. Ideally, a more sophisticated cost function that estimates the expense of a given plant modification should be used. The robotic manipulator case study presented in this article uses change in mass to approximate plant modification cost:

$$\phi(\mathbf{x}) = \sum_{i=1}^{n_c} |m_i(\mathbf{x}) - \hat{m}_i|,$$

where n_c is the number of plant components being modified, $m_i(\mathbf{x})$ is the mass of component i with modification defined by $\mathbf{x}$, and $\hat{m}_i$ is the mass of component i in the baseline design. This simplified metric is used to estimate the cost of limited plant redesign to the manufacturer. A more complete study would include full lifecycle cost, including use (such as energy and maintenance costs) and end-of-life costs.

2.5. *Multi-objective optimization*

If the performance requirements are flexible, the engineer may wish to explore the tradeoff between performance and plant redesign cost. This tradeoff information is especially useful if the design objective is to improve system performance at a reasonable cost, and can be obtained via solution

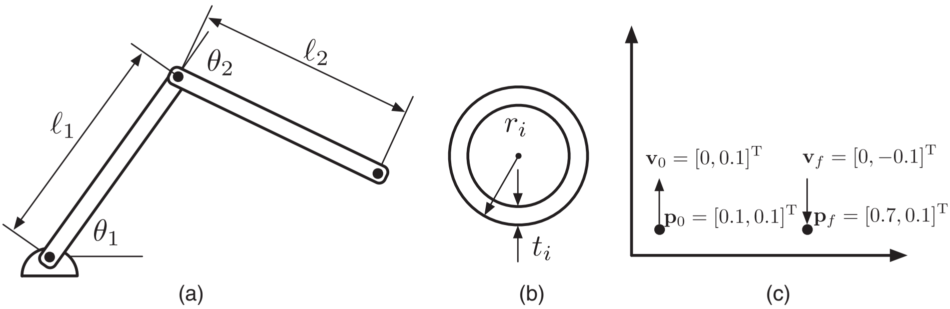

Figure 1. (a) Two-link planar manipulator. (b) Section view of link i. (c) Task A initial and final conditions.

of a multi-objective optimization problem:

$$\begin{aligned} \min_{\mathbf{x}=[\bar{\mathbf{x}}_\mathbf{p},\mathbf{x}_\mathbf{c}]} \quad & \left\{\phi(\mathbf{x}), \psi(\mathbf{g}_\mathbf{r}(\mathbf{x}))\right\} \\ \text{s.t.} \quad & \mathbf{g}_\mathbf{p}(\mathbf{x}) \leq 0. \end{aligned} \tag{4}$$

Here, the scalar cost metric described above $\phi(\mathbf{x})$ is minimized simultaneously with $\psi(\mathbf{g}_\mathbf{r}(\mathbf{x}))$, the maximum normalized performance violation. The solution to this problem is a Pareto set that provides insight into the tradeoff between cost and requirement satisfaction, which is useful in determining whether some relaxation of performance requirements is worth the associated cost savings.

The Pareto set also illustrates the predicted minimum performance degradation if no plant design changes are made, *i.e.*, $\|\bar{\mathbf{x}}_\mathbf{0} - \bar{\mathbf{x}}_\mathbf{p}\| = 0$. This is useful quantitative evidence an engineer can use to support the case for limited plant design changes. If the cost of not meeting requirements exceeds the cost of plant changes required to satisfy requirements, then proceeding with a limited plant redesign is justified.

3. PLCD of a robotic manipulator

Robotic manipulators are used extensively in manufacturing, and manipulator energy efficiency and dynamic performance are important economic and environmental considerations (Field and Stepanenko 1996; Li *et al.* 2001; Sato *et al.* 2007). The PLCD example presented here involves a two-link planar manipulator that is designed to perform a specific pick-and-place task (Task A) with minimal energy consumption while complying with joint actuator torque and link deflection constraints. This baseline design is obtained using co-design, and represents the existing mechatronic system an engineer seeks to modify to perform a new task (Task B). It is shown that the baseline design is incapable of meeting Task B requirements through control design changes alone. Sensitivity analysis is used to identify a limited set of plant modifications, and then the PLCD problem is solved to identify a limited plant redesign that can perform Task B while complying with requirements. PLCD is also compared to full system redesign.

Figure 1(a) illustrates the manipulator configuration. Position is specified by the two joint angles θ_1 and θ_2 (in the position shown, $\theta_2 < 0$). Each link has a constant annular cross section with radius r_i and wall thickness t_i (Figure 1(b)) and is constructed of 7075 T6 aluminium. Figure 1(c) illustrates Task A initial and final conditions. The manipulator is to lift a 20 kg payload from the initial position $\mathbf{p}_0$ with initial velocity $\mathbf{v}_0$, and $t_f = 2.0$ s later place the payload at $\mathbf{p}_f$ with final velocity $\mathbf{v}_f$.

The original system is designed to perform Task A with minimal energy based on the following co-design formulation:

$$\begin{aligned} \min_{\mathbf{x}=[\mathbf{x_p},\mathbf{x_c}]} \quad & E(\mathbf{x}) \\ \text{s.t.} \quad & |\tau_{\max,i}(\mathbf{x})| \leq \tau_{\text{allow}}, \quad i = 1,2 \\ & \delta_i(\mathbf{x_p}) \leq \delta_{\text{allow}}, \quad i = 1,2, \end{aligned} \tag{5}$$

where $E(\mathbf{x})$ is the total mechanical energy consumed to perform the assigned task, $\tau_{\max,i}(\mathbf{x})$ is the maximum joint i torque, τ_{allow} is the allowable torque (limited by joint actuators), $\delta_i(\mathbf{x_p})$ is the maximum link deflection for a given nominal torque, and δ_{allow} is the upper deflection bound. Here, the actuator design is assumed to be fixed, resulting in a torque bound of $\tau_{\text{allow}} = 210\,\text{Nm}$. The full plant design vector here includes the two link lengths and the link section radii: $\mathbf{x_p} = [\ell_1, \ell_2, r_1, r_2]^{\text{T}}$.

The desired (quintic) trajectory for the joint angles $\mathbf{q_d}(t) = [\theta_1(t), \theta_2(t)]^{\text{T}}$ is calculated based on the initial and final positions and velocities given in Figure 1(c), as well as the position $\mathbf{p}_I$ and velocity $\mathbf{v}_I$ of an intermediate point along the path between $\mathbf{p}_0$ and $\mathbf{p}_f$. A feedback linearization approach with proportional and derivative control (Spong, Hutchinson, and Vidyasagar 2005) was used to track $\mathbf{q_d}(t)$. Joint torque trajectories and energy consumption computed using inverse dynamics agreed with feedback linearization, allowing the omission of tracking control design variables and simplification of the problem formulation. Using inverse dynamics instead of forward simulation results in a reduced set of control design variables, which includes only the intermediate position and velocity values required to define the desired trajectory:

$$\mathbf{x_c} = [p_{I1}, p_{I2}, v_{I1}, v_{I2}]^{\text{T}},$$

i.e., the control optimization portion of the system design problem has been reduced to finding the minimum energy trajectory, parameterized by the intermediate trajectory point $\mathbf{x_c}$.

The following nonlinear differential equation was used to model manipulator dynamics:

$$\mathbf{M}(\mathbf{q}, \mathbf{x_p})\ddot{\mathbf{q}} + \mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}, \mathbf{x_p})\dot{\mathbf{q}} + \mathbf{g}(\mathbf{q}, \mathbf{x_p}) = \boldsymbol{\tau}, \tag{6}$$

where $\mathbf{M}(\mathbf{q}, \mathbf{x_p})$ is the inertia matrix, $\mathbf{C}(\mathbf{q}, \dot{\mathbf{q}}, \mathbf{x_p})$ computes the centrifugal and Coriolis terms, and $\mathbf{g}(\mathbf{q}, \mathbf{x_p})$ is the gravity vector. Definition of these terms for the two link manipulator can be found in Spong, Hutchinson, and Vidyasagar (2005). Note that each of these terms depend on both joint position and plant design. The joint torque vector is $\boldsymbol{\tau} = [\tau_1, \tau_2]^{\text{T}}$. In this model joint motor mass, motor rotational inertia and electrical losses have been neglected. Energy is calculated by integrating the mechanical power at each joint, but no energy recapture is counted (*i.e.*, no regenerative braking). Complete details of the model may be found in the supplementary MATLAB® code for this article (Allison 2012b).

The deflection constraint can be shown to be active using monotonicity analysis (Papalambros and Wilde 2000), and radius values may be eliminated from $\mathbf{x_p}$ by substitution of the active constraints (simplifying the plant design problem). The deflection constraint is satisfied implicitly, and the reduced-dimension design vector is $\mathbf{x_p} = [\ell_1, \ell_2]^{\text{T}}$. More specifically, given ℓ_i, the minimum value of r_i that satisfies the deflection constraint can be calculated. Here, it is assumed that the nominal torques are $\boldsymbol{\tau_n} = [140, 80]^{\text{T}}\,\text{Nm}$, $\delta_{\text{allow}} = 4\,\mu\text{m}$, link wall thicknesses are $t_1 = 3\,\text{mm}$ and $t_2 = 2\,\text{mm}$, the elastic modulus is $E = 71.7\,\text{GPa}$, and material density is $\rho = 2810\,\text{kg/m}^3$ to calculate radius values:

$$r_i = \frac{2\tau_{ni}\ell_i^2}{3\pi E t_i \delta_{\text{allow}}} + \frac{t_i}{2}. \tag{7}$$

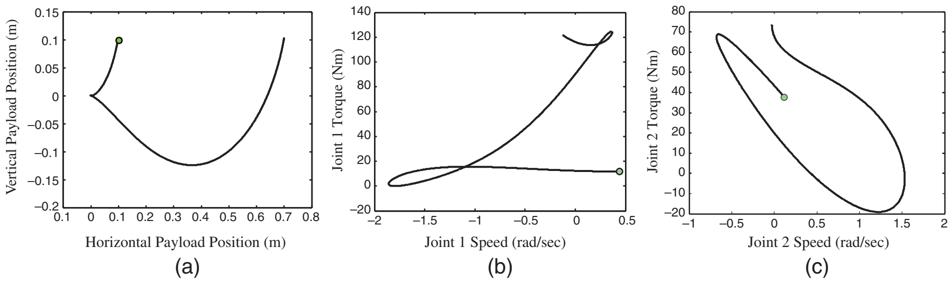

Figure 2. Nominal plant design results: (a) payload trajectory; (b) joint 1 and (c) joint 2 torque–speed trajectories.

3.1. *Task A co-design*

The solution of the co-design problem given in Problem (5) for Task A is presented in this section, and the role of passive dynamics in reducing energy consumption is discussed. The resulting design is used as a baseline system design that represents the existing system to be modified via PLCD. For comparison and to demonstrate the value of co-design, the performance of a nominal plant design ($\mathbf{x_p} = [0.6, 0.6]^{\mathrm{T}}$ m) that represents a design solution obtained through conventional means (*i.e.*, a sequential approach where plant design obtained via expert engineering intuition followed by control optimization[†]) will first be considered. The minimum energy trajectory for the nominal design is $\mathbf{x_c} = [0.183, -0.0836, 0.0146, 0.142]^{\mathrm{T}}$, which results in the payload path illustrated in Figure 2(a). Figures 2(b) and 2(c) illustrate the torque–speed trajectories for each of the joints; the circle indicates the starting point at the initial time t_0.

Both joint actuators stay well within the bound $\tau_{\text{allow}} = 210$ Nm. The payload trajectory follows a 'falling' type motion, exploiting to some degree the passive dynamics of the baseline plant design to perform Task A using only 21.3 J of energy. The torque at joint 1 remains near zero for much of the simulation; joint 2 is more active.

Understanding and harnessing the intrinsic dynamics of a physical system (Pitti and Lungarella 2006; Rieffel *et al.* 2010) can help reduce control forces and energy inputs. Rather than using joint control to force the manipulator to follow a specific path, it is allowed to follow the passive trajectory as much as possible, exerting relatively small control torques to guide the payload into the right position at the right time. Taking this idea to the extreme, McGeer (1990) demonstrated a passive walking device that required no active input—only gravitational potential energy—to maintain steady-state walking. Collins *et al.* (2005) used simple power sources to replace gravity for passive walkers, enabling them to walk on flat ground or inclines with energy efficiency magnitudes better than conventional robotic walkers. Williamson (2003) applied this principle to a variety of other robotic systems, explaining that using passive dynamics instead of ignoring or canceling them can be particularly beneficial for specialized or repetitive tasks.

Ahmadi and Buehler (1999) classified the use of passive dynamics as a biomimetic principle that can be used to reduce energy consumption in dynamic systems. There is one important distinction between previous studies in passive dynamics and biological systems; the former fixes physical system design and addresses only control design, whereas physical and control system properties co-evolve in biological systems (Chiel and Beer 1997; Valero-Cuevas 2009). In this article robotic design is taken a step closer to the elegance of biological systems by designing physical and control systems together in a way that exploits synergy between these design domains. The nominal design

[†] Optimization problems throughout this article were solved using a hybrid approach where a gradient-based method (SNOPT [Gill *et al.* 1997]) is applied after a gradient-free method (pattern search with a global search method [Audet and Dennis 2006]). The first step provides a good starting point for SNOPT and improves the probability of finding a global optimum.

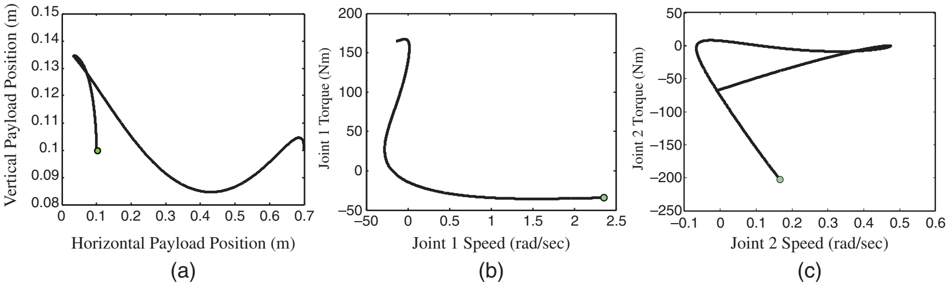

Figure 3. Task A system-optimal design: (a) payload trajectory; (b) joint 1 torque–speed trajectory and (c) joint 2 torque–speed trajectory.

represented in Figure 2 is efficient, but can be improved by tailoring the physical system to the requirements of Task A. This improvement is realized by solving the simultaneous co-design problem given in Problem (5). The resulting trajectories are system-optimal, and are illustrated in Figure 3.

The payload takes a fundamentally different path with the system-optimal design; joint torques remain close to zero for much of the simulation. The total energy consumption is a remarkably low 0.0272 J. The optimal design is

$$\mathbf{x_p} = [1.77, 1.63]^{\mathrm{T}}, \quad \mathbf{x_c} = [0.113, 0.121, 0.0503, -0.437]^{\mathrm{T}}.$$

The links more than doubled in length, a counterintuitive result. The system mass is higher, but energy consumption decreased. In this case the centre of mass location and kinematics were ideal for Task A; customized passive dynamics enabled task completion with very little control effort. While τ_2 is at its bound at t_0, it is much smaller afterwards. Also note that, for Task A, the link length ratio is again near unity so that $\mathbf{p}_0$ is reachable.

It should be emphasized that because Task A does not include a return of the end effector to the start position, the energy consumption reported here is not indicative of continuous repeated operation. Co-design is still expected, however, to enable identification of the minimum-energy system design for repeated operation, likely exploiting the change in mass and inertia properties from releasing the payload to make the return path more energetically favourable.

A parametric study was performed to explore the influence of task time t_f on system performance. Holding the plant design fixed at the system optimal value of $\mathbf{x_p} = [1.77, 1.63]^{\mathrm{T}}$, task time was varied from 0.3 to 2.0 s and the optimal trajectory was computed for each task time (Figures 4 and 5).

Figure 4(a) reveals the dependence of energy consumption on task time. As expected, energy consumption and t_f are inversely related. Energy consumption is nearly constant between $t_f = 1.0$ and 2.0 s, indicating that passive dynamics dominate and very little control intervention is required in this range. Below this range more energy is required because the manipulator must move faster than passive dynamics allow. Figures 4(b) and 4(c) illustrate the joint torque trajectories for a range of task time values. Trajectories for $t_f < 0.6$ s are omitted owing to large magnitudes that would obscure the other trajectories.

Figure 5(a) illustrates the payload trajectories for a range of task times. Trajectories undergo a fundamental change in shape as task time dips below one second. Above this value the payload is first lifted in a way that exploits passive dynamics. Below one second the passive dynamics are too slow, and the payload takes a more direct (forced) path. The torque–speed curves for $t_f = 0.6$ and $t_f = 2.0$ s, shown in Figures 5(b) and 5(c), illustrate that longer task times (which are more aligned with passive dynamics) result in torque trajectories closer to zero for a greater portion

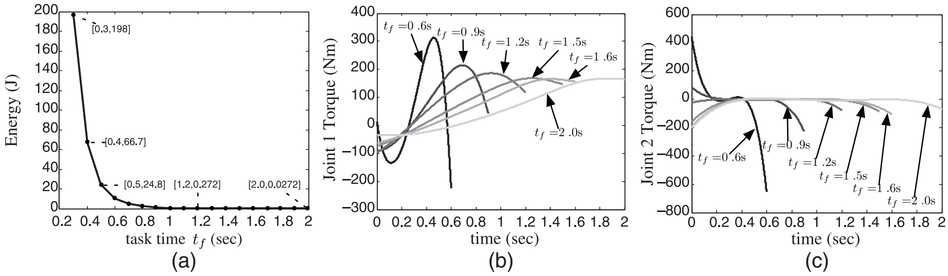

Figure 4. Task A parametric study: (a) energy consumption as a function of task time; (b) joint 1 and (c) joint 2 actuator torques for various task times.

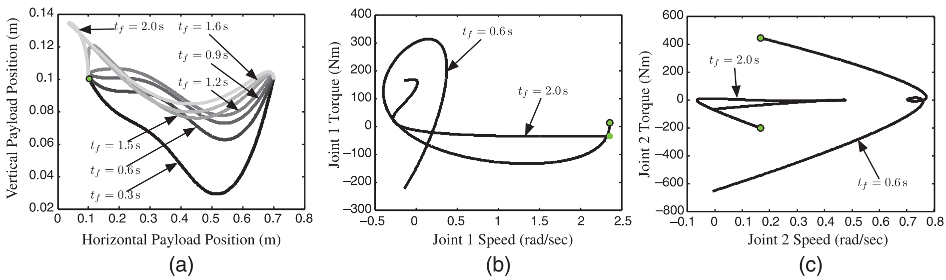

Figure 5. Task A parametric study: (a) payload trajectory as a function of task time; (b) joint 1 and (c) joint 2 torque–speed trajectories for $t_f = 0.6$ and $t_f = 2.0$ s.

of the task. Observing proximity to zero torque is one way to identify whether passive dynamics dominate system behaviour.

Keep in mind that in this parametric study the plant design was held fixed. Except for $t_f = 2.0$ s, this plant design is not system-optimal. Had co-design been performed for each t_f value, the energy consumption and torque values would be lower as the passive dynamics would be better matched to the task. There is still a lower task time limit for physical systems below which passive dynamics cannot be used; below this limit active control must dominate since passive dynamics are incapable of sufficiently fast motion.

3.2. *Task B co-design*

Here the performance of the Task A system-optimal plant design for a new task (Task B) will be explored, and it will be verified that this plant design is incapable of meeting torque requirements through control system (trajectory) design changes alone. For comparison, a new system design for Task B (*i.e.*, clean-sheet design for the new task) will be presented for comparison to PLCD results. This approach reveals the best possible performance for Task B, but this complete system redesign comes at a cost that may be prohibitive. The next step, described in the following subsection, involves co-design with limitations on plant redesign as a strategy to reduce system modification cost.

The new task (Task B) involves significant vertical displacement, and is defined by the following boundary conditions:

$$\mathbf{p}_0 = [0.5, 1.2]^{\mathrm{T}}\ \mathrm{m}, \quad \mathbf{v}_0 = [-0.1, 0]^{\mathrm{T}}\ \mathrm{m/s},$$
$$\mathbf{p}_f = [0.4, 2.0]^{\mathrm{T}}\ \mathrm{m}, \quad \mathbf{v}_f = [-0.1, 0]^{\mathrm{T}}\ \mathrm{m/s}.$$

If the manipulator links were massless, the energy required to perform Task B could not be less than $m_p gh = (20\,\text{kg})(9.81\,\text{m/s}^2)(0.8\,\text{m}) = 157\,\text{J}$. Values lower than this are possible if the total mass centre at the initial position is higher than the payload, or if the total mass centre at the final position is lower than the payload. This highlights the one influence of plant design on potential system performance.

Holding the optimal plant design from Task A co-design fixed while optimizing the joint trajectories $\mathbf{q}(t)$ for Task B, the minimum energy consumption is 116 J. For the joint actuators from the baseline design to be reused, the maximum torque constraint of $\tau_{\text{allow}} = 210\,\text{Nm}$ must be satisfied. Unfortunately, the maximum joint torques here are $\tau_{1\,\text{max}} = 210\,\text{Nm}$ and $\tau_{2\,\text{max}} = 401\,\text{Nm}$, illustrated in Figures 6(b) and 6(c). This result confirms that the *Task A plant design is incapable of performing Task B while satisfying torque requirements*. It can be shown by parametrically adjusting torque limits and iteratively solving the optimal trajectory problem that actuators capable of 382 Nm of torque are capable of getting the Task A baseline plant design to perform Task B successfully; actuators with torque values less than this will not be capable of completing Task B using the Task A plant design.

Observe from Figure 6 that passive dynamics are not exploited; torque values remain far from zero. Task B performance clearly can be improved by redesigning the entire system specifically for Task B requirements, although this may be a costly option. To provide an upper performance bound and allow comparison with PLCD results, the manipulator was completely redesigned using full co-design (*i.e.*, both link lengths modified) to perform Task B with minimum energy. The minimum energy consumption obtained using co-design was 52.6 J, and the optimal system design for Task B is

$$\mathbf{x_p} = [2.28, 1.14]^{\mathrm{T}}, \quad \mathbf{x_c} = [0.691, 1.52, -0.758, -0.0618]^{\mathrm{T}}.$$

Referring to Figure 7(a), the trajectory is fundamentally different. The Task A plant design was optimized earlier for a specific falling motion, which is evident in Figure 6(a), whereas the more direct Task B co-design trajectory is much more efficient for Task B. The longer (and no

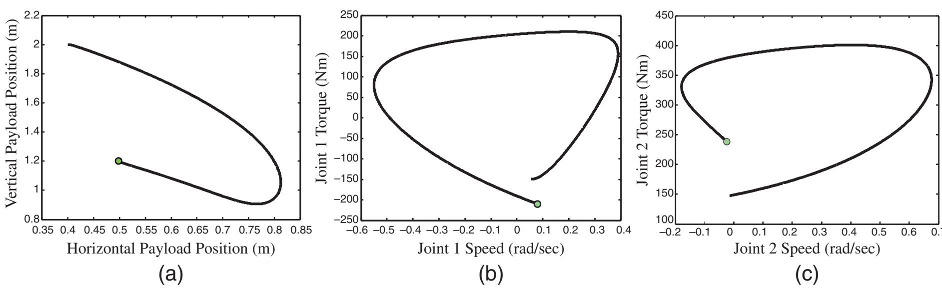

Figure 6. Task B using Task A plant design: (a) payload trajectory; (b) joint 1 and (c) joint 2 torque–speed trajectories.

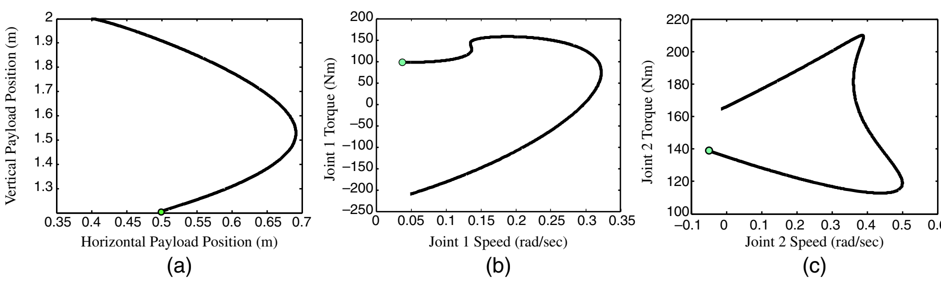

Figure 7. Task B co-design results: (a) payload trajectory; (b) joint 1 and (c) joint 2 torque–speed trajectories.

longer similar) link lengths place the system mass centre to the upper left of the payload, enabling the payload to be hoisted into position using passive dynamics to some degree. While the torque values illustrated in Figures 7(b) and 7(c) are not near zero, they are significantly lower than when using the Task A plant design.

3.3. *Plant-limited co-design for Task B*

The Task B co-design result performed well, but was costly. Change in link mass is used as a proxy cost function. The link lengths in the Task B co-design increased significantly, resulting in a redesign cost of 14.5 kg. Here PLCD will be applied to obtain a system design for Task B that meets requirements while minimizing the cost of plant design changes.

Step 1 in the PLCD process is to identify candidate plant design changes. The plant design in this system has been simplified to two design variables, so a limited plant redesign will involve changing either ℓ_1 or ℓ_2 (a more sophisticated limited plant redesign example can be found in a companion article [Allison 2012a]). When attempting to use the Task A plant design to perform Task B, it was discovered that the first torque constraint was active and the second was violated. In PLCD the torque constraints will be satisfied at lower cost by identifying, using sensitivity analysis, which of the two design variables would be most effective at reducing both maximum joint torques.

Both the $\partial \bar{g}_{ri}(\mathbf{p})/\partial p_j$ and $\partial C(\mathbf{p})/\partial p_j$ terms for Equation (2) were computed using finite differences, where $\bar{g}_{ri}(\mathbf{p})$ are the torque constraint violations and $C(\mathbf{p})$ is the change in mass from the Task A baseline design. Having gone through the Task A co-design process, a complete system model that accommodates the independent design variables is available (which is normally not the case), so $\mathbf{x_p}$ can be used directly in the sensitivity analysis instead of $\mathbf{p}$. The resulting cost Jacobian is:

$$\mathbf{J_c} = \begin{bmatrix} \dfrac{\partial \bar{g}_{r1}(\mathbf{p})}{\partial c_1} & \dfrac{\partial \bar{g}_{r1}(\mathbf{p})}{\partial c_2} \\ \dfrac{\partial \bar{g}_{r2}(\mathbf{p})}{\partial c_1} & \dfrac{\partial \bar{g}_{r2}(\mathbf{p})}{\partial c_2} \end{bmatrix} = 10^3 \times \begin{bmatrix} 0.205 & -1.10 \\ -0.00758 & 0.0525 \end{bmatrix} \text{Nm/kg.}$$

The first column indicates how sensitive joint torque violation is with respect to the cost of changing ℓ_1 (approximated using mass), and the second column expresses this sensitivity for ℓ_2. Clearly, link 2 length is dominant, so the rest of the PLCD process is based on a plant redesign that consists only of ℓ_2 as the candidate plant design variable. In problems with more sophisticated plant design problems, the set of candidate plant design variables would normally be larger than one (Allison 2012a). Note that some candidate plant design variables may go unchanged during the optimization step (Step 3) of the PLCD process, particularly if there is a large step increase of cost for any non-zero change of a plant design variable.

The second step in the PLCD process specifies the development of a more complete system model that incorporates dependence on candidate plant design variables. A complete system model is already available from Tasks A and B co-design, so this step can be skipped here. Normally a model like this is not available; engineers at this stage will have a model useful only for control design, and would need to put forth significant effort to develop a model that relates independent design variables to control design model parameters.

In addition to solving Problem (3) for this example, a parametric study on ℓ_2 was performed to illustrate the tradeoffs involved in this PLCD problem. Figure 8(a) illustrates the relationship between ℓ_2 and energy consumption, as well as maximum joint torque values. This figure shows that choosing ℓ_2 as the candidate plant design variable results in a large feasible domain for the PLCD problem ($0.48 \leq \ell_2 \leq 1.10$ m). In other words, not only is it possible to meet Task B

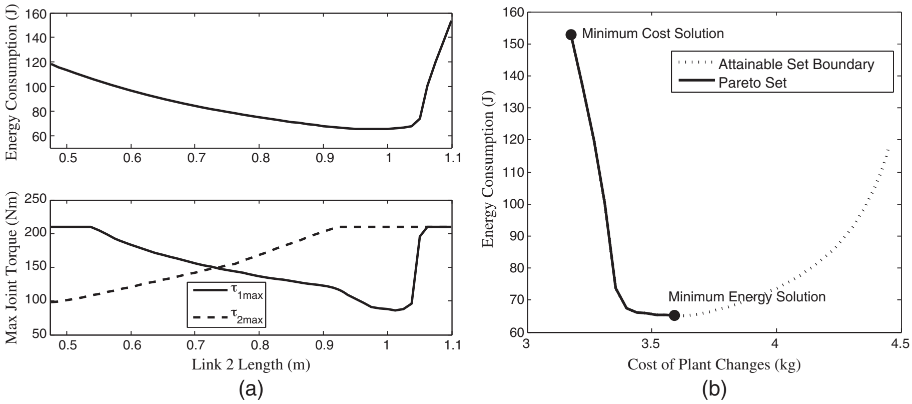

Figure 8. PLCD for Task B: (a) parametric study on ℓ_2; (b) Pareto set illustrating cost–energy tradeoff.

requirements by varying only ℓ_2, but many options exist, providing the opportunity to reduce cost further. The minimum-cost design that solves Equation (3) is $\ell_2 = 1.10$ m. This is the feasible design that is closest to the original length of ℓ_2 from the Task A design (1.63 m) (see Figure 8(a)). The (proxy) cost of changing ℓ_2 to 1.10 m is 3.17 kg. If instead minimum energy design is sought, the result is $\ell_2 = 0.975$ m. This comes at the price of a small cost increase to 3.59 kg, but reduces energy consumption from 154 to 65.2 J.

Figure 8(b) illustrates the tradeoff between plant change cost and energy consumption. At the upper left end of the curve is the minimum-cost solution, but from this Pareto set it is clear that energy consumption can be reduced significantly with only nominal cost increases. The dashed line indicates the boundary of the attainable set that does not lie on the Pareto frontier. Note that in this case the use of a complete lifecycle cost metric for $\phi(\mathbf{x})$ that includes redesign, use (energy), and end-of-life costs is an alternative to multi-objective optimization, although tradeoff information can be useful in supporting the decision to make limited plant design changes.

Figure 9 illustrates the payload and torque–speed trajectories for the minimum-cost design resulting from the Task B PLCD solution. The payload trajectory is fairly similar to the trajectory associated with using the Task A design for Task B. Torque does not remain near zero, indicating passive dynamics do not play a large role in system response. Passive dynamics become more significant when switching to the minimum energy solution ($\ell_2 = 0.975$ m, trajectory not shown). Maximum torque for both joints in the minimum-cost solution is 210 Nm, meeting Task B requirements.

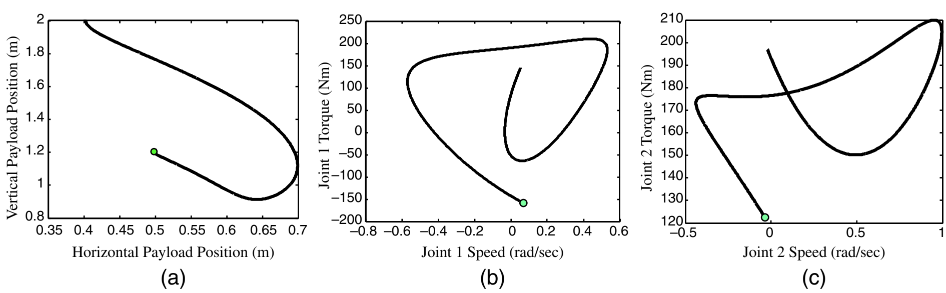

Figure 9. Task B PLCD results: (a) payload trajectory; (b) joint 1 and (c) joint 2 torque–speed trajectories.

Given the simplicity of plant design here, it can be verified that ℓ_2 was the correct choice for limited plant redesign by investigating the outcome of choosing ℓ_1 instead. Choosing ℓ_1 as the candidate plant design variable does result in a feasible PLCD problem, but the feasible domain is very narrow ($0.42 \leq \ell_1 \leq 0.45$ m), plant modification cost is higher (minimum cost is 10.0 kg), and energy consumption is much higher (354 J). In this case the sensitivity-based approach to selecting candidate plant modifications succeeded. Other more sophisticated approaches for selecting candidate plant modifications should be explored, including those that address change propagation through a system more thoroughly (Giffin *et al*. 2009).

Table 1 summarizes the numerical results of the robotic manipulator case study. For Task A, co-design reduced energy consumption significantly, utilizing passive dynamics of the physical system. Completely redesigning the system for Task B using co-design resulted in the lowest energy consumption for Task B (52.6 J), but came at a plant modification cost of 14.5 kg. Redesigning only link 2 (identified during Step 1 of PLCD) using co-design to minimize energy consumption resulted in energy consumption of 65.2 J, an increase of only 24%, but at 75.2% lower cost. Applying PLCD to task B (minimum cost) resulted in an even lower 3.17 kg modification cost, but increased energy consumption to 154 J. The tradeoff between energy consumption and cost may be evaluated using the Pareto set illustrated in Figure 8(b) to determine whether a design between the minimum-cost PLCD result and the minimum energy design would be appropriate. Finally, it was confirmed that sensitivity analysis predicted correctly that choosing ℓ_2 as the limited redesign variable would produce the best results. Choosing ℓ_1 instead resulted in significantly higher energy consumption for Task B at a cost nearly as high as full redesign.

4. Discussion

As engineering system scale and complexity increase, limited system redesign (as opposed to designing from scratch) is becoming more commonplace. In the redesign of mechatronic systems, engineers often seek to meet performance requirements for new applications through control design changes alone. While usually less expensive than physical design changes, control design changes alone may be insufficient. If control system modification is inadequate, limited physical system design changes should be investigated since complete system redesign may be impractical.

In this article a solution was proposed for mechatronic system repurposing that involves a limited redesign of the physical system (plant). Here a subset of plant components are selected for redesign, reducing plant modification cost. The limited plant and control design changes could be made using a traditional sequential approach, or a 'co-design' approach could be used where plant and control design changes are considered simultaneously to produce a superior system-optimal design. The latter approach, detailed in this article, is the first formal methodology for plant-limited co-design, *i.e.*, an integrated approach for solving the system repurposing problem

Table 1. Summary of robotic manipulator design results.

	$\mathbf{x_p}$	Energy (J)	Cost (kg)
A nominal $\mathbf{x_p}$	$[0.60, 0.60]^T$	21.3	–
A co-design	$[1.77, 1.63]^T$	0.0272	–
B co-design	$[2.28, 1.14]^T$	52.6	14.5
B PLCD ($\bar{\mathbf{x}}_\mathbf{p} = \ell_2$, min E)	$[1.77, 0.975]^T$	65.2	3.59
B PLCD ($\bar{\mathbf{x}}_\mathbf{p} = \ell_2$, min cost)	$[1.77, 1.10]^T$	154	3.17
B PLCD ($\bar{\mathbf{x}}_\mathbf{p} = \ell_1$, min cost)	$[0.45, 1.63]^T$	354	10.0

with limited plant changes. Candidate plant design changes are identified using sensitivity analysis, and optimization is used to solve the resulting Plant-Limited Co-Design (PLCD) problem. It was shown that the sensitivity analysis did lead to the correct candidate plant modifications using a robotic manipulator design example. In this example the objective was to perform a specific manipulation task in a prescribed amount of time while minimizing energy consumption and satisfying deflection and torque constraints. The manipulator design example also demonstrated the effectiveness of co-design for exploiting passive system dynamics to reduce energy consumption.

The primary contribution here is the development of a formal approach for solving mechatronic PLCD problems. This approach may be viewed as an intermediate step for industry toward full-system co-design. Engineering firms may be reluctant to embrace co-design methods for ground-up development of new mechatronic systems; PLCD, however, may be easier to adopt because of reduced model development requirements, smaller adoption investment, and rapid realization of co-design benefits. PLCD can aid in reducing cost, energy consumption, and material usage in the development of mechatronic systems by supporting the reuse of existing systems. PLCD also has value beyond repurposing; systems that perform poorly for their original task may be improved via limited system redesign.

Formalization of a limited redesign approach for mechatronic systems establishes PLCD as a new design paradigm and generates numerous opportunities for future work. The example presented here involved a simplified physical system design; several questions still need to be addressed, including how to accommodate topological plant design changes such as adding, removing, or replacing components in addition to modifying existing components. In the manipulator example, the control architecture was assumed to be the same in the modified system; future work should address topological changes to control architecture in Steps 2 and 3 of PLCD. More accurate cost modelling is needed, and the sensitivity analysis used here may not work for system design problems with a larger or more complicated model or design space. Here an early-stage control design approach was used; future work may involve detailed control design decisions, observer design, or sensor/actuator placement. Finally, the PLCD strategy may be extensible to other systems requiring redesign besides mechatronic systems.

5. Conclusion

In summary, PLCD is a promising new area of mechatronic design that supports the repurposing of existing systems for new applications or improving underperforming systems. It has the potential to produce significant cost, energy and material savings, and is easier for practitioners to implement than full system co-design. Continued development of PLCD methodology and application to new case studies should be pursued to enhance the ability to design and manage increasingly complex engineering systems.

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